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ABSTRACT

Structural changes in an English as a Second Language (ESL) 30-item reading comprehension test were examined through principal components analysis on a small sample (n=31) of students. Tests were administered on three occasions during intensive ESL training. Principal components analysis of the items was performed for each test occasion. Permutation tests, based on 1,000 replications, were used to test the significance of eigenvalues and loadings. Null factor structures were simulated by randomly and independently permuting the column elements of each data set. The first eigenvalues were significant on all three test occasions. Long reading passage items loaded significantly. The first eigenvalue increased in size over the three test administrations. An appendix contains the source listing of the Statistical Analysis System test used to perform the permutation test. (Contains 4 tables and 13 references.) (Author/SLD)

Permutation Tests in Principal Component Analysis

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of the

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Abstract

Structural changes in an English as a second language (ESL) 30-item reading comprehension test were examined with principal components analysis on a small sample (n=31)of students. Tests were administered on three occasions during intensive ESL training. Principal component analysis of the items was performed for each test occasion. Permutation tests, based on 1000 replications, were used to test the significance of eigenvalues and loadings. Null factor structures were simulated by randomly and independently permuting the column elements of each data set. The first eigenvalues were significant on all three test occasions. Long reading passage items loaded significantly. The first eigenvalue increased in size over the three test administrations.

Factor analysis is the tool of choice to explore the underlying structure of tests. Statistical inference in factor analysis is commonly performed with parametric goodness-of-fit tests (Kendall, Stuart & Ord, 1983, p. 328-332; Loehlin, 1987, p. 62-64) where multivariate normality is assumed. These tests are also based on asymptotic expressions which are most accurate in large samples. It is reasonable to question the use of these inference methods on small, non-normal data sets. Nonparametric statistics are targeted at these problematic situations. This paper illustrates the use of nonparametric permutation tests on factor analyses of small, binary variable data sets.

Permutation Tests

Permutation, or randomization tests, are based on probability statements derived solely from observed data sets. They are robust, nonparametric tests because no assumptions about theoretical sampling distributions are needed. Permutation tests are conceptually simple and lend themselves to solution by simple computer algorithms. Fisher (1960, p.13) used a permutation test to illustrate the concept of a null hypothesis test. One of the earliest and most complete descriptions of randomization tests is provided by Edgington (1969a, Chapter 5) in which examples are given for tests of means, differences between means, proportions and correlations. Modern desktop computers can perform these tests in a matter of minutes.

Suppose a researcher measures two variables, X and Y, on each of 7 cases, and computes the Pearson

correlation, (r_{obs}). A test of Ho: rho = 0 could be performed by creating a sampling distribution of r where each sample r was calculated on a separate permutation of the values of Y. There are 5040 (7!) distinct permutations of the 7 Y values. A sampling distribution of r with 5040 samples could be generated where r = 0. If all 5040 permutations of Y are performed, E(r) = 0 and var(r) = 1/(n-1) (Kendall and Stuart,1979, pp. 501-503). These are essentially the same parameters of the distribution of r for normally distributed samples. In effect, the permutation distribution of r becomes a sampling distribution of r under Ho: rho = 0. The Pth percentile r value (r_P)from the 5040 permuted samples serves as a critical value for a one-tailed, alpha = (1-P/100) test. Upper and lower percentiles of the permutation distribution of r could be used similarly to define two-tailed critical values.

Full-blown permutation tests become impractical as n increases. If n were 20, 20! (2.4329 x 1018) distinct permutations of Y are possible. Further, in multivariate studies the number of distinct permutations also depends on the number of variables. A data matrix of n rows and p columns produces $n!^{p-1}$ distinct permutations. The data matrices for this study had n=31 cases and p=30 variables, yielding $31!^{29}$ (8.2228 x 1029957) unique permutations. In order to use this method in most practical situations, one must randomly sample from the possible permutations (Edgington,1969b). Tests based on randomly sampled permutations are called approximate permutation tests.

Darlington (1990, pp. 368-369) presents permutation tests as robust alternatives to linear model tests. Darlington found that permutation tests produce accurate tests of regression parameters under nonnormality, but were less accurate under heteroscedasticity. Hays (1996) studied permutation tests of the correlation coefficient (Ho: rho = 0) and found them to have better control of type I error rates, compared to the parametric t test, under extreme nonnormality and small sample sizes.

Application of Permutation Tests to Factor Analysis

Two null hypotheses were addressed with permutation tests in this study, (a) Ho: *R* = I and (b) Ho: $a_{ij} = 0$. Ho: *R* = I, where *R* is the correlation matrix and I is an identity matrix of the same order, implies that all variables are uncorrelated; there are no common factors. This hypothesis will be tested by comparing the observed eigenvalues with critical values from the distribution of 1000 randomly permuted samples. The test of Ho: $a_{ij} = 0$, where aij is the factor loading (structure coefficient) for variable i on factor j, evaluates the significance of the contribution of Xi to the factor. This test will be performed by comparing the observed factor loadings to critical values from the distribution of loadings from 1000 randomly permuted samples.

The permutation tests reported here follow the methods of Buja and Eyuboglu (1992). Buja and Eyuboglu examined permutation tests as a form of parallel analysis in principal components analysis. Parallel analysis was proposed by Horn (1965) as a factor analysis inference tool. Horn's parallel analysis was performed by comparing observed factor analysis results with those obtained on randomly simulated data sets. Computer simulated independent, normal deviates were generated to create a random data matrix of the same order as the observed data matrix. Eigenvalues from the observed and parallel data sets were compared to perform significance tests. Scree plots of the observed and random eigenvalues were constructed. If an observed eigenvalue was larger than the corresponding randomly generated eigenvalue, it was deemed significant.

Later applications of parallel analysis used critical values from large simulated sampling distributions of eigenvalues, rather than one simulated sample (Longman, Cota, Holden & Fekken; 1989). Buja and Eyuboglu (1992) used permutation samples rather than simulated normal deviates to perform parallel analysis.

Zwick and Velicer (1990) empirically compared many of the standard rules for determining the number of common factors in a correlation matrix. Parallel analysis; along with the Scree Test, goodness-of-fit tests, Kaiser's eigenvalue 1 rule and residual correlation analysis; were examined for their ability to accurately estimate the number of latent factors. Parallel analysis was found to be the most accurate method for determining the number of dimensions in data sets.

Application of Permutation Tests to a Reading Comprehension Test

The data for this analysis consisted of the scored responses (1 = correct, 0 = incorrect) of 31 English as a second language (ESL) students on a 30 item reading comprehension test. Test items presented subjects with a reading passage and then questions were posed about the passage. The test was administered three times during intensive ESL training. Test results were analyzed using classical item analysis and analysis of variance. There were significant reading comprehension improvements. A significant item x occasion interaction was also observed. In addition to these analyses, the researchers wanted to examine changes in the factor structure of the tests.

Principal component analysis was chosen to explore the structure of the reading comprehension tests because of its simplicity and absence of latent structural assumptions. Communalities do not have to be estimated and no assumptions about the underlying distributions of the variables need to be made. Further, Velicer and Jackson (1990) have shown that the various forms of common factor analysis and principal component analysis produce the same structural solutions, as long as the same number of dimensions and rotational criteria are used.

Each 31-subject by 30-item data set was subjected to a principal component analysis. Critical values of significance tests for eigenvalues and loadings were estimated from a distribution of eigenvalues and loadings computed on 1000 permuted samples of the original data. Programs were written in FORTRAN and IML (SAS Institute, 1989) to generate and analyze the permuted data sets. Copies of these programs are provided in the appendix of this paper.

A permuted sample was created by randomly and independently permuting the column values of an observed data set. After each column was randomly shuffled, a principal component analysis was performed. Eigenvalues and loadings from 1000 permuted samples were archived and used for significance testing. The 95th and 99th percentile eigenvalues and loadings from the permuted samples

Results

Table 1 presents the observed eigenvalues for the three test occasions (early, middle and late instruction) along with the 95th and 99th percentile eigenvalues from the 1000 permuted samples. The first eigenvalues from all three occasions were significant at the .01 level. The second eigenvalue from the first occasion was significant at the .05 level but not at the .01 level. If a Bonferroni correction (alpha = .05/3 = .0167) for multiple tests is made, the second eigenvalue from the first occasion is not significant.

The loadings on the first principal component from the permuted samples were used to estimate the .05 and .01 alpha level critical values. The permuted sample loadings were transformed to absolute values to perform one-tailed tests on the loadings; only positive loadings are meaningful in this example. An item having a negative loading should be removed from the test, because subjects failing that item scored higher on the test. This result usually indicates that an item is incorrectly keyed. However, no significant negative loadings were observed.

Tables 2, 3 and 4 present the first component loadings from the three testing occasions along with the 95th and 99th percentile loadings from the permuted samples. Critical values of approximately .61 and .71 respectively were required at the .05 and .01 levels of significance. Inspection of the loadings revealed that the significant loadings were observed among the later items in the test, and these items had the longest reading passages.

Conclusions

This study examined the use of permutation tests of hypotheses in exploratory factor analyses of a reading comprehension test administered on three occasions to students in an intensive ESL program. Tests of dimensionality indicate a strong single factor. The first test yielded a significant second factor at the .05 level, but it was not a significant when a Bonferroni correction for multiple tests was used. It was concluded that the dimensionality of the test did not change during the ESL program.

Permutation tests applied to the loadings indicated that the most salient items were those associated with long reading passages. This result occurred on all three testing occasions. It was concluded that questions linked to longer reading passages were more discriminatory on the general factor.

Permutation tests using standard computer packages were found to be useful inference tools. Because of their simplicity, these tests offer a flexible alternative to parametric, linear model tests.

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Table 1. Principal Component Eigenvalues for the Three Test Occasions and the 95th and 99th Percentiles from 1000 Randomly Permuted Samples

	Test 1			Test 2			Test 3		
Item	P95[1]	P99[2]	Obs[3]	P95	P99	Obs	P95	P99	Obs
1	3.892	4.097	4.335	3.894	4.114	4.859	3.870	4.043	5.275
2	3.325	3.467	3.427	3.314	3.433	2.767	3.300	3.412	3.290
3	2.930	3.049	2.704	2.944	3.054	2.607	2.922	3.032	2.896
4	2.622	2.714	2.36	2.637	2.744	2.368	2.625	2.712	2.487
5	2.374	2.457	2.244	2.377	2.452	2.144	2.368	2.439	2.191
6	2.142	2.225	1.732	2.154	2.236	1.995	2.16	2.236	1.801
7	1.946	2.009	1.570	1.943	2.018	1.861	1.946	2.024	1.526
8	1.765	1.803	1.467	1.762	1.832	1.592	1.777	1.840	1.445
9	1.602	1.657	1.396	1.592	1.646	1.442	1.613	1.666	1.283
10	1.453	1.506	1.266	1.443	1.495	1.313	1.441	1.502	1.098
11	1.302	1.351	1.071	1.308	1.358	1.128	1.296	1.341	0.983
12	1.165	1.217	1.056	1.166	1.201	1.049	1.169	1.215	0.970
13	1.041	1.082	0.904	1.043	1.091	0.721	1.041	1.085	0.783
14	0.921	0.963	0.734	0.929	0.992	0.651	0.928	0.967	0.652
15	0.817	0.861	0.649	0.816	0.864	0.560	0.823	0.873	0.631
16	0.721	0.756	0.545	0.715	0.757	0.494	0.711	0.754	0.526
17	0.625	0.666	0.461	0.622	0.652	0.447	0.626	0.660	0.436
18	0.536	0.579	0.434	0.536	0.570	0.384	0.540	0.567	0.381
19	0.458	0.489	0.403	0.459	0.498	0.353	0.456	0.493	0.312
20	0.387	0.413	0.365	0.388	0.414	0.321	0.389	0.422	0.247
21	0.319	0.346	0.236	0.322	0.352	0.221	0.317	0.350	0.181
22	0.259	0.286	0.196	0.260	0.290	0.207	0.260	0.284	0.153
23	0.210	0.236	0.156	0.208	0.227	0.173	0.203	0.233	0.143
24	0.161	0.179	0.117	0.160	0.178	0.125	0.158	0.175	0.113
25	0.118	0.138	0.067	0.119	0.131	0.072	0.119	0.137	0.089
26	0.084	0.097	0.050	0.083	0.094	0.057	0.083	0.094	0.050
27	0.053	0.067	0.028	0.054	0.064	0.050	0.053	0.066	0.041
28	0.03	0.042	0.017	0.031	0.040	0.034	0.031	0.038	0.014
29	0.013	0.018	0.009	0.013	0.017	0.004	0.014	0.019	0.003
30	0.003	0.006	0.000	0.003	0.005	0.003	0.003	0.006	0.000

1 - 95th percentile eigenvalue from the randomly permuted samples.
2 - 99th percentile eigenvalue from the randomly permuted samples.
3 - Eigenvalues on the observed data set.

Table 2. Factor Loadings on Factor 1 for Test 1 Along with P95 and P99 from the Permuted Samples

	Observed Loadings	1000 Permuted Sample Critical Values	
Item	Test 1	P95	P99
1	-0.313	0.608	0.718
2	0.106	0.605	0.694
3	0.030	0.597	0.731
4	0.305	0.612	0.726

5	0.025	0.616	0.693
6	0.056	0.594	0.710
7	-0.033	0.601	0.710
8	-0.300	0.611	0.698
9	-0.063	0.631	0.732
10	0.340	0.612	0.724
11	0.384	0.620	0.707
12	-0.139	0.600	0.714
13	0.558	0.597	0.704
14	0.005	0.616	0.721
15	0.490	0.618	0.719
16	0.550	0.627	0.711
17	0.172	0.635	0.726
18	0.099	0.615	0.726
19	0.172	0.638	0.737
20	0.361	0.627	0.747
21	-0.027	0.620	0.705
22	0.513	0.610	0.720
23	0.520	0.608	0.739
24	0.445	0.602	0.720
25	0.617*	0.603	0.709
26	0.516	0.621	0.692
27	0.371	0.596	0.698
28	0.650*	0.619	0.707
29	0.780**	0.628	0.712
30	0.387	0.605	0.686

* = p < .05
** = p < .01

Table 3. Factor Loadings on Factor 1 for Test 2 Along with P95 and P99 from the Permuted Samples

Item	Observed Loadings Test 2	1000 Permuted Sample Critical Values P95	P99
1	0.097	0.614	0.732
2	0.367	0.602	0.727
3	0.302	0.599	0.702
4	0.429	0.596	0.700
5	0.151	0.604	0.733
6	-0.137	0.631	0.722
7	0.067	0.615	0.706
8	0.466	0.608	0.725
9	0.395	0.632	0.721
10	0.220	0.625	0.717
11	-0.348	0.626	0.729
12	0.493	0.595	0.702
13	0.308	0.620	0.699
14	0.232	0.603	0.701
15	0.364	0.600	0.718
16	-0.196	0.613	0.704
17	0.207	0.633	0.713
18	0.266	0.611	0.728
19	0.291	0.635	0.725
20	0.274	0.600	0.709
21	-0.540	0.606	0.712
22	0.364	0.613	0.713
23	0.539	0.631	0.718
24	0.748**	0.615	0.707
25	0.547	0.617	0.716

26	0.379	0.596	0.710
27	0.502	0.626	0.741
28	0.644*	0.613	0.716
29	0.520	0.600	0.715
30	0.600	0.620	0.718

* = p < .05
** = p < .01

Table 4. Factor Loadings on Factor 1 for Test 3 Along with P95 and P99 from the Permuted Samples

Item	Observed Loadings Test 3	1000 Permuted Sample Critical Values P95	P99
1	0.407	0.633	0.723
2	0.413	0.591	0.672
3	0.269	0.614	0.723
4	0.434	0.595	0.688
5	0.288	0.630	0.702
6	0.331	0.619	0.735
7	-0.333	0.607	0.701
8	0.447	0.610	0.716
9	0.342	0.613	0.730
10	0.357	0.613	0.714
11	-0.007	0.616	0.723
12	0.087	0.598	0.706
13	0.270	0.613	0.681
14	0.372	0.641	0.727
15	0.515	0.603	0.722
16	0.134	0.610	0.705
17	0.533	0.632	0.731
18	0.148	0.588	0.701
19	0.418	0.602	0.715
20	0.554	0.610	0.688
21	0.194	0.604	0.703
22	0.181	0.618	0.719
23	0.250	0.630	0.714
24	0.418	0.617	0.702
25	0.351	0.616	0.711
26	0.802**	0.614	0.722
27	0.307	0.603	0.736
28	0.704*	0.607	0.713
29	0.690*	0.620	0.718
30	0.708**	0.612	0.693

* = p < .05
** = p < .01

Appendix

Source Listing of the SAS IML Program to Perform a Permutation Test on Principal Component Statistics.

```
* permute.sas

This program randomly permutes the columns of a data matrix and can be used to perforn
permutation tests on  principal component statistics.  Principal components analysis
is performed on the permuted data sets. Eigenvalues and loadings  of the permuted samp
are output.

Critical values for the permutation tests can be obtained from  the distributions of
```

```
permuted results. Output files 'outeigen'  and 'outload' contain the eigenvalues and
loadings from the  permuted samples. For example, a one-tailed test of significance
with alpha = .05 could be performed using the 95th percentile eigenvalue computed
on the permuted samples

;

data one;                    * Input observed data;
options ls= 70;
infile 'data';
input (x1-x30) (30*1.);      * Formatted input of observed data;
proc iml;                    * Begin iml procedure;
use one;                     * Store the file from data step one as
                               matrix x;
read all into x;
tx = x;                      *  tx = temporary copy of x;
tx2 = x;                     *  tx2 = another copy of x;
nrep = 1000;                 *  nrep = number of permuted samples;
rand = j(nrow(x),1,0);       *  rand = vector of random deviates;
load = j(nrep,ncol(x),0);    *  storage for loadings onfirst factor
                                only;
eigen = j (nrep,ncol(x),0); *  storage for eigenvalues;
 do k = 1 to nrep;
  do i = 1 to ncol(x);
  rand = uniform(rand);
  tr = rank (rand);
   do j = 1 to nrow(x);
   tx2[j,i] = tx [tr[j],i];   * tx2 is a randomly permuted x;
   end;                       * end j loop;
  end;                        * end i loop;

 n=nrow(tx2);                 * Begin computing correlation matrix;
 sum= tx2[+,];
 xpx = t(tx2)*tx2-t(sum)*sum/n;
 s=diag(1/sqrt(vecdiag(xpx)));
 corr = s*xpx*s;              * End correlation calculation ;
 call eigen(e,v,corr);
 v1 = v[,1];
 l1 = v1*sqrt(e[1]);
 eigen[k,] = t(e);
 load[k,] = t(l1);
 end;                         * end k loop ;
filename out 'outeigen';      * 'outeigen' stores the eigenvalues;
file out;
do i = 1 to nrow(eigen);
do j = 1 to ncol(eigen);
put (eigen[i,j])  8.3 @;
end;
put;
end;
closefile out;
filename out2 'outload';      * 'outload' contains the loadings;
file out2;
do i = 1 to nrow(load);
do j = 1 to ncol(load);
put (load[i,j])  7.3 @;
end;
put;
end;
closefile out2;
```

Fortran program to permute randomly columns of a data matrix.

```
C      MODIFIED FOR MWERA 06/14/99
C      INPUT FILE = ONE OF K. PERKINS THREE TEST DATA SETS
```

```
C      OUTPUT FILE = 19 RANDOMLY PERMUTED DATASETS
C      IX = INTEGER CASE INDEX, R  = RANDOM NUMBER ~U(0,1)
C      X = OBSERVED SCORE MATRIX
C      PX = RANDOMLY PERMUTED SCORE MATRIX
C      N = SAMPLE SIZE, NV = NUMBER OF VARIABLES
C      NP = NUMBER OF PERMUTED SAMPLES
       INTEGER IX(100,50)
       REAL  R(100,50), X(100,50), PX(100,50)
C      READ NV AND THE DATA MATRIX X
       NV = 30
       N=31
       DO 20 I=1,N
   20  READ (3,21) (X(I,J), J=1,NV)
   21  FORMAT (30F1.0)
       ISEED = 93942211

       DO 500 II = 1,1000
       DO 100 J = 1,NV
          DO 100 I = 1,N
          CALL RANDU (ISEED, JSEED,R(I,J))
          IX(I,J) = I
  100  CONTINUE

C      BUBBLE SORT BY COLUMN FOR RANDOM PERMUTATION
       DO 200 K = 1,NV
          DO 200 I = 1,N
             DO 200 J = I+1, N
             IF (R(I,K).LE.R(J,K)) GO TO 200
             TEMPR = R(I,K)
             ITEMPX = IX(I,K)
             R(I,K) = R(J,K)
             IX(I,K) = IX(J,K)
             R(J,K) = TEMPR
             IX(J,K) = ITEMPX
200    CONTINUE

C      CREATE PERMUTED SCORE MATRIX - PX
       DO 300 J = 1,NV
          DO 300 I = 1, N
300       PX(I,J) = X (IX(I,J),J)

C      OUTPUT PERMUTED SCORE MATRIX
       DO 400 I=1,N
400     WRITE(8,420)II, (PX(I,J), J=1,NV)
420    FORMAT (I4,30F2.0)

500    CONTINUE
       STOP
       END
       SUBROUTINE RANDU(IX,IY,R)
       L1=5**15
       L2=2**30
       IY=MOD(IX*L1,L2)
       R = ABS( FLOAT(IY) / FLOAT(L2))
       IX=IY
       RETURN
       END
```

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